Agricultural productivity and land inequality. Evidence from the Philippines

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Abstract

This paper presents the first detailed empirical evaluation of the effect of genetically engineered (GE) crops on land inequality, using three waves of census data covering 21 years and 17 million plots in the Philippines. Exploiting exogenous variations in soil and weather characteristics leading to differences in potential gain from GE corn cultivation, I show that the introduction of this labor-saving technology in 2003 led to an increased in municipality-level landholding and land ownership inequality. This effect is partly driven by a relative increase in agricultural land, is stronger in municipalities that adopted modern agricultural practices later and where credit penetration is higher. While increased land inequality is associated with a higher level of terrorist activity, it does not seem to have any adverse effect on agricultural productivity or economic activity.

***JEL* Classification: O13, Q12, Q14, Q15**
Keywords: Land inequality, Agricultural technology, Land reform

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1 Introduction

The structure of a country's agricultural sector is strongly linked to its development level. In low-income countries, it is characterized by a large number of smallholder farmers while in high-income countries, farms tend to be larger and fewer[1]. This difference can be explained by the process of structural transformation, whereby workers move out of agriculture into the industrial and the service sectors. This implies a substantial reallocation of agricultural land between those who leave and those who stay. How this reallocation takes place shapes the land inequality and ultimately has an impact on the distribution of income and wealth at the national level.

Gains in agricultural productivity have been identified as a key driver of this structural transformation as they reduce the demand for agricultural labor and increase the demand for manufacturing goods. While there has been an extensive literature studying the impact of agricultural productivity on land expansion (see Villoria et al. (2014) for a review), its effect on land inequality has so far remained unaddressed. This is striking given that an often-heard reproach of modern agricultural technologies is that they favor large farms, at the expense of smallholder farmers, leading to an increase in land concentration. These claims are especially common for genetically engineered (GE) crops but are rarely backed by data or only based on very loose empirical analysis (Catacora-Vargas et al., 2012; Phélinas and Choumert, 2017). Herbicide tolerance and pest resistance - the two main traits in GE crops - are labor saving as they decrease the need of manual weeding and pesticide spraying respectively. As Bustos et al. (2016) show, this kind of labor-augmenting technology is the one driving structural transformation and is therefore likely to lead to a redistribution of agricultural land. Moreover, the higher return on capital is likely to favor better-off farmers and lead to higher levels of inequality.

This paper presents the first empirical evaluation of the causal effect of GE crops on land inequality, using a proper identification strategy. It focuses more precisely on the introduction of GE corn in the Philippines in 2003. I take advantage of the fact that agricultural land is an immobile asset, meaning that the largest part of the aggregate inequality is to be found at the very local level. The analysis therefore uses municipality-level inequality measures, which gives a large enough number of observations to allow the use of traditional microeconometric tools and identify causal effects. Such an approach would not be possible with income or wealth inequality, which are characterized by a much larger between-municipality component as individuals with similar levels of income or wealth tend to cluster together.

Most of the literature on land distribution in economics focuses on the impact of land inequality rather than on its drivers. The most compelling argument for a more equal land distribution comes from a series of papers, starting with Alesina and Rodrik (1994), showing a negative correlation between inequality - especially land inequality - and economic growth[2]. Historical evidence suggests that this

[1] Using agricultural census data from 92 countries, Lowder et al. (2016) find that farms smaller than 2 ha account for 30-40% of land in low- and lower-middle-income countries and less than 10% in upper-middle- and high-income countries.

[2] See also Easterly (2007); Fort (2007), Neves et al. (2016) and Cipollina et al. (2018) for meta-analyses

is driven by lower investment in physical and human capital in areas with unequal land distribution[3]. Likewise, land redistribution policies have been shown to decrease poverty in India (Besley and Burgess, 2000), South Africa (Keswell and Carter, 2014) and the Philippines (Reyes, 2002; World Bank, 2009). This may be due to the fact that a more equal distribution generates more employment per hectare (and per unit of output) as small sized farms are more labor intensive and access to land provides a safety net which may encourage non-farm business investment (Binswanger-Mhkize et al., 2009). Furthermore, as agricultural activity in developing countries exhibits diseconomies of scale - the so-called "inverse farm size-productivity" -, redistributing land to smallholder farmers may lead to efficiency gains. This finding is supported by Vollrath (2007) who finds a negative relationship between land Gini and agricultural productivity. However, this claim has recently been challenged by Foster and Rosenzweig (2017) who show that the relationship between farm productivity and farm scale is in fact U-shaped and that large farms are as efficient as small ones, even in developing countries[4].

Land inequality has also been linked with an increased likelihood of conflict (de Luca and Sekeris, 2012; Peters, 2004; Thomson, 2016), environmental degradation (Ceddia, 2019; Sant'Anna, 2016) and reduced resilience against natural disasters (Anbarci et al., 2005)[5]. Despite this large number of studies on the – mostly negative – effects of land inequality, there exists surprisingly little research on its drivers One notable exception is Bardhan et al. (2014) who use rich panel data from West Bengal to show that household division is a much larger contributor of land inequality than land market transactions or the land reform. At a more aggregate level, Lowder et al. (2016) and Jayne et al. (2016) also provide a detailed description of agricultural land distribution, respectively for the whole world and in four African countries.

Using three waves of census data covering 21 years and 17 million plots this paper document the change in national and municipality-level landholding inequality in the Philippines before and after the introduction of GE corn in 2003. First, I show that landholding inequality increased between 2002 and 2012, despite an ongoing land reform aimed at redistributing agricultural land. A Theil's inequality decomposition reveals that within-municipality inequality accounts for 80% of total inequality. Changes in national inequality are therefore highly likely to be driven by changes at that level and the rest of the empirical analysis takes the municipality as unit of observation[6].

[3] Banerjee and Iyer (2005); Baten and Hippe (2018); Cinnirella and Hornung (2016); Galor et al. (2009)

[4] Similarly, Adamopoulos and Restuccia (2019) find that land redistribution during the agrarian reform in the Philippines led to a 17% decrease in productivity.

[5] See also Guereña and Wegerif (2019) for a recent multi-disciplinary review.

[6] Agricultural censuses are the most commonly-used data source to investigate land inequality, going back to Deininger and Squire (1998). In a recent paper however, Bauluz et al. (2020) have advocated for the use of household surveys instead. They show that, while both data sources give comparable land Gini coefficients, adjusting for the landless population and the land value – both absent from census data – leads to important changes in inequality measures. While agricultural censuses do have shortcomings, they also offer the extensive coverage needed for the kind of analysis carried out in this paper. Indeed, computing land inequality indicators at the local level (municipality or even village) using household surveys would be highly imprecise given the low number of households typically surveyed in each location. Moreover, household surveys only take into account household farms and therefore systematically miss company-owned farms which tend to be larger. As an extreme example, Lowder et al. (2016) show that in Guatemala, the 2% largest farms from the agricultural census, representing 57% of total land, are absent from the LSMS household survey.

As the census data does not distinguish between GE and non-GE corn, it is not possible to correlate the use of the technology with land inequality measures. Moreover, such a measure would be subject to reverse-causality bias. Indeed, it is not clear whether a positive correlation would mean that higher adoption rate leads to higher land concentration or simply that the technology is adopted more in places where land is less equally distributed. To overcome this identification issue, I take advantage of exogenous variation through space and time. First, I compare data collected in 2002 – one year before GE seeds were commercialized – with data from 2012, in a first-difference setting, similar to a municipality fixed effects model. Second, I exploits differences in local soil and weather characteristics to compute an exogenous variation in profitability from GE corn, an approach taken from Bustos et al. (2016)[7]. This allows to compare the change in land inequality across municipalities which benefited a lot from the technology and those which only benefited marginally. Results show that the new technology increases total farm area, as well as the share of land planted in corn. In addition, landholding inequality increased in municipalities that benefited more from GE corn, an effect driven by the top of the distribution. I also find suggestive evidence that land *ownership* inequality increased with the introduction of GE crops, although ownership inequality indicators that can be obtained from the census data are less precise.

I then investigate potential mechanisms and show that the effect disappears when we control for the change in agricultural land, implying that the increase in inequality occurs mainly through a relative increase in farm land. Finally, two interesting heterogeneous effects are investigated. First, the effect is stronger in municipalities that adopted modern inputs later, i.e. where the potential for yield increase was the highest. Second, it is larger in places with more credit penetration ten years before the seeds commercialization. This brings support to claims made by advocacy groups that the high input costs associated with the new technology pushes farmers to take usurious loans from informal moneylender, with interest rates as high as 10 percent per month. According to anecdotal evidence, many farmers who default become bankrupt and need to forego or sell their land, usually to the financier, thereby increasing land concentration (Masipag, 2013).

To assess to robustness of the results, a series of tests are presented. First, controlling for additional topographical and geographical characteristics does not have a substantial impact on the result. Second, a placebo test comparing 1991 and 2002 data fails to find a similar effect and shows that, if anything, municipalities that benefited more from the technology were on a trend towards less inequality before the introduction. Third, the results remain significant when spatial correlation is taken into account using Conley standard errors and when standard errors are clustered at the provincial level. Finally, running the analysis at the level of the barangay (village) gives the same results, especially when the sample is restricted to rural areas.

Contrasting with our results, GE crops have been found to be beneficial to farmers in developing

[7] Similar estimation strategies has been used in other related papers such as Dias et al. (2019); Moscona (2019)

countries, increasing household income and farm profits[8]. Given the large literature documenting the adverse effects of land inequality, the net effect of the technology appears uncertain, although the inequality effect is unlikely to offset all the productivity gain. In the last part of the paper, I investigate the correlation between land inequality and three measures of socio-economic welfare: agricultural productivity, night light intensity and terrorist activity. Contrary to the earlier analysis, this part does not claim to identify any causal relationship as we do not have any exogenous variation of land inequality – and the potential yield measure cannot be used as an instrument given the obvious violation of the exclusion restriction. The socio-economic outcomes of land inequality are mixed. On the one hand municipalities where land inequality increased experienced higher growth of agricultural productivity and night light intensity. On the other hand, terrorist activities measured as the number of attacks and the number of casualties at the provincial level are positively correlated with land inequality. This suggests that the welfare costs of higher inequality are low on average, but may increase in less politically stable regions.

The question of the distributional impacts of agricultural technology is actually not new in economics and echoes an old literature studying the distributive effects of the Green Revolution, especially in South Asia[9]. These papers however relied on very limited data sources, usually from a few hundred households. Moreover, they only focused on describing the change in inequality and did not rely on causal identification strategies. The present work therefore addresses an old question using modern empirical tools. In addition, it contributes to the above-mentionned land inequality literature, extending it towards the identification of causal drivers of inequality dynamics. Finally, it is also linked to the literature on agricultural productivity and structural transformation, in particular Bustos et al. (2016)[10]. Results presented in this paper can therefore be seen as a description of the land redistribution process resulting from a more structural change of the economy.

2 Backgroud

The Philippines is an archipelago composed of 7,641 islands, situated in South-East Asia with a total land area of 300,000 square kilometers. During the period considered in this paper, 1991-2012 it was considered as a lower-middle income country, with a share of employment in agriculture declining from 45% to 32% (World Bank, 2019). Despite sustained economic growth and a strong decline in overall poverty, poverty incidence remained high in rural areas, as 57% of agricultural households were characterized as poor in 2009, three times the proportion of non-agricultural households (Tabuga et al., 2012). Moreover, the country is characterized by a high level of income, wealth and land inequality, owing to the legacy of Spanish colonialism which constituted a landed elite class occupying prominent

[8]See Qaim (2016) for a recent review and meta-analysis; Yorobe and Smale (2012) and Mutuc et al. (2013) for the case of GE corn in the Philippines.

[9]Bardhan (1974); Chaudhry (1982); Freebairn (1995); Otsuka et al. (1992); Prahladachar (1983); Raju (1976)

[10]Note that, while the new corn variety described in Bustos et al. (2016) is a land-augmenting technology, the introduction of GE corn in the Philippines was likely labor-augmenting and is more comparable to that of GE soy in their paper.

positions in the country political and economic apparatus. This high level of inequality is at the root of the civil conflicts that have beset the country in the past decades, among which the Moro insurgency on the island of Mindanao (McDoom et al., 2019).

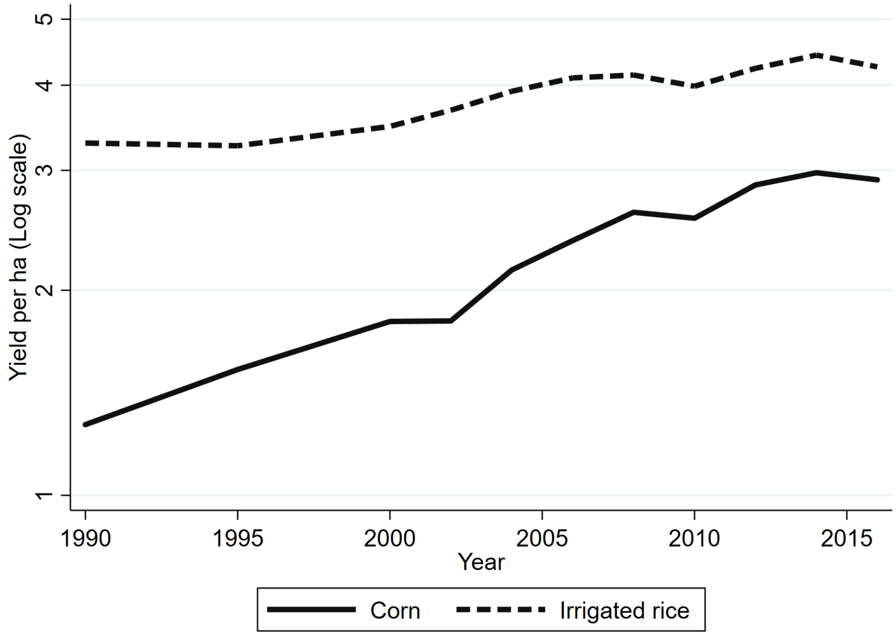
In an effort to address the issue of land inequality, the country has undergone a series of land reforms since the beginning of the twentieth century. The most recent one, the Comprehensive Agrarian Reform Program (CARP), started in 1988 with a triple objective of equity/social justice, farm efficiency and poverty reduction. The scope of this reform was extensive as it covered all agricultural land with a few exceptions[11]. Both tenants and regular farm workers were included as recipients, as long as they were landless or smallholder farmers (with less than 3 ha of land). The reform put an upper limit on ownership of agricultural land at 5 ha, plus 3 ha per heir of minimum 15 years at the time of the reform, provided that they were willing to continue tilling or managing the farm. Thirty years after the start of the implementation, the CARP claims to have redistributed 4.8 million hectares to 2.8 million households (Ballesteros et al., 2017). These figures are unrealistically high given that, according to the agricultural census, there were 3.76 million farmers in the Philippines in 1991 and that when we add up the land area under leasehold and tenancy with the area owned in excess of 5 ha, we only reach 4.1 million ha. If the redistribution numbers are true, we would therefore observe a much larger decrease in land inequality than what is found in the subsequent censuses. In addition, several scholars have criticized the reform implementation process for being captured by the landed elite and resulting in little distribution of wealth and power to the landless and smallholder farmers (Borras, 2006; Borras et al., 2007; Lanzona, 2019).

Corn is the second most-cultivated crop in the country. It is used both for consumption and sold to the booming animal feeds industry. In 2003, the country approved the commercialization of GE corn seeds. Farmers were fast to adopt this new technology and, by 2014, 62% of the hectarage devoted to corn was planted with GE seeds (ISAAA, 2017). The first generation of biotech corn included the *Bacillus thuringiensis* (Bt) trait, which confers the plant pest tolerance. In 2005, new varieties were commercialized exhibiting herbicide tolerance (Ht) as well. In 2012, the overwhelming majority of GE corn planted in the Philippines had both traits (Bt/Ht)(Aldemita et al., 2014).

Figure 1 shows the evolution of corn and rice yield per hectare between 1990 and 2016, using official data from the Department of Agriculture. In the decade following the introduction of GE corn, corn yield almost doubled. Such a large gain in productivity was not observed in rice, the main crop of the Philippines. In line with the global literature on GE crops (Qaim, 2016), two papers have shown that GE corn is beneficial to the farmers. Yorobe and Smale (2012) use an instrumental variable strategy to account for adoption and find that it increases net farm income by USD 105 per hectare and monthly off-farm income by USD 49 through a reduction in labor requirements. This highlights the labor-saving effect of the technology. Heterogeneous effects estimated by Mutuc et al. (2013) with propensity score

[11] Exceptions include military reservations, penal colonies, educational and research fields, timberlands, undeveloped hills with 18 degrees slope and church areas.

Figure 1: Temporal evolution of corn and rice yield



Source: Bureau of Agricultural Statistics (2005, 2008, 2013); Philippine Statistics Authority (2018)

matching show that the farmers benefiting the most are smaller, poorer and less likely to adopt biotech seeds.

3 Data

3.1 Agricultural census

3.1.1 Data harmonization

This paper uses the latest three waves of the Census of Agriculture and Fisheries (CAF), collected in 1991, 2002 and 2012 by the Philippine Statistical Agency (PSA), under the supervision of the FAO's World Census of Agriculture. The data provides plot-level information including size, tenure status, main use and the crops cultivated over the past year. Harvest and input information were unfortunately not collected except for some very coarse measures of input use in 1991. Given small differences in the sampling method, farm definition and the type of data collected, we need to be careful when comparing the three waves. In what follows, I briefly explain the two most important differences and how they are addressed. A more detailed description of the data cleaning process can be found in Appendix A.

Farms are defined at the level of the household. This implies that several operators working independently from each other but living together (e.g. a father and a son) are considered as one farming unit.

In the rest of the paper, farms and farming households are therefore used interchangeably. In addition, we only take into account farms with a total land area of at least 0.1 ha, a cutoff used in the 2002 census. This ensures that the temporal variations we find in the land distribution are not the result of changing farm definitions and that the households considered devote a significant amount of resources to their farming activity.

The first major difference between CAF waves is that only the last one provides a complete enumeration of all the farms in the country. In 1991 and 2002, a sample of barangays was drawn within each municipality thanks to a systematic sampling method using information from the previous agricultural and population censuses. All farming households living in the sampled barangays were then enumerated. Sampling weights allow the computation of municipality-level statistics and are used in all the empirical analysis.

Another difference between CAF waves is that the location of the plot is reported at the barangay level in 1991 and 2012 and only at the larger, municipality level in 2002. This information is important as we are interested in the distribution of agricultural land, which needs to be computed over a given geographic area. A first possibility might be to run the analysis according to the farmer's residence, as plots are usually located within walking distance from the place of living. However, this approach is problematic for two reasons. First, when we speak of land distribution, we are intuitively refering of the distribution of the land located in the area of study, not of the land farmed by households living in that area. Second, farms cultivated by people living far from their plots or extending beyond administrative boundaries, are likely to be systematically different from the others. For example, agricultural land distribution in urban areas is not a relevant issue, whereas absentee landlords living in urban areas may have a non-trivial effect on the land distribution where their farm is located. For this reason, land distribution measures are computed based on the physical location of the plot and not on the residence of its operator. This analysis is carried out at the municipality level as this is the lowest level reported in the three waves[12].

The CAF also reports the land tenure status of each plot, which I divide between ownership (full ownership, owner-like possession and various forms of community ownership) and tenancy (rental, leasehold, rent free occupation). As in other agricultural censuses, when the farmer is a tenant, we do not have any information regarding the owner of the plot. Indicators of land inequality therefore measure land holding inequality and not land ownership inequality[13].

[12] In addition, the incompleteness of the CAF1991 prevents from computing barangay-level statistics based on plot location. Indeed, we systematically miss the information from households living in non-sample barangays. For non-sample barangays, this means that we only have information on the land cultivated by outsiders. In sampled barangays, we potentially miss many of the outsiders. As farms spreading over administrative boundaries are likely to differ systematically from the others, this would create biases in our land distribution measures. Taking the plot municipality instead solves this problem as all municipalities are enumerated.

[13] As noted by Vollrath (2007), landholding inequality matters for efficiency while land ownership inequality is more relevant from an equity perspective

3.1.2 Land distribution across farms

The distribution of agricultural landholdings in the Philippines is described in Table 1. The total land devoted to agriculture increased over the first decade from 8.6 to 9.6 million ha and then strongly decreased in the second decade to 7.5 million ha. This pattern is driven by a strong increase in farm number between 1991 and 2002 and a steady decrease in average farm size over the whole period, which was probably driven by the land reform. In addition, total population strongly increased over the period, from 60 to 92 million inhabitants, while the share of rural population remained relatively constant, around 50%. This strong demographic expansion increased the pressure on land and may also explain part of the decline in farm area.

Table 1: Summary statistics of national land distribution

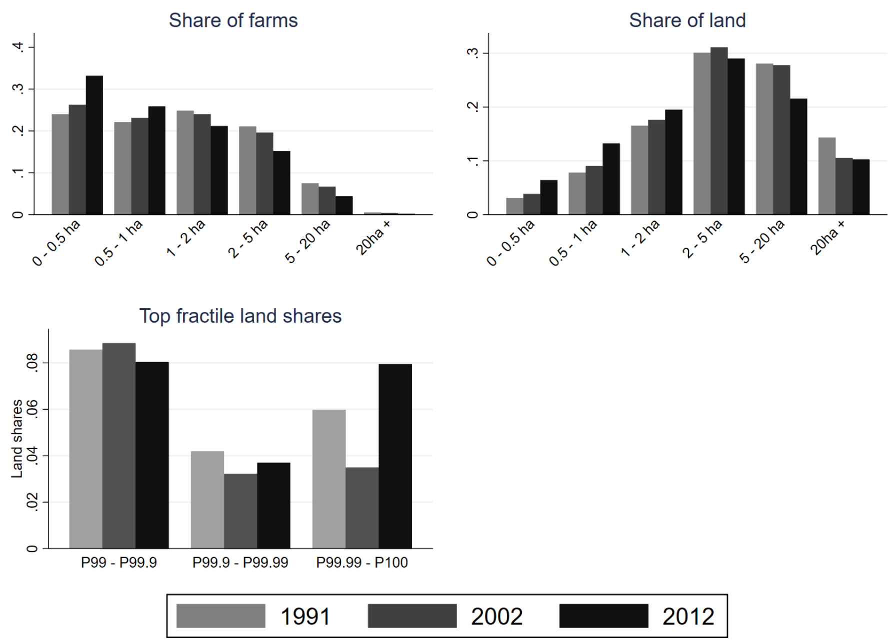
	1991	2002	2012
Agricultural area (million ha)	8.57	9.56	7.56
Number of farms	3.76 million	4.8 million	4.55 million
Average farm size (ha)	2.28	1.99	1.64
Landholding Gini	0.590	0.576	0.606
Share top 1%	18.73%	15.34%	19.68%
Share top 10%	46.85%	44.86%	48.02%
Share bottom 50%	13.10%	13.74%	12.32%
Share tenanted land	34.07%	31.19%	27.80%
Share tenanted farms	31.01%	25.30%	25.75%
Population (million)[a]	60.703	75.698	92.100
Share of rural population[a]	51.3%	48.9%	50.9%

Source: Philippine Statistics Authority - Census of Agriculture and Fisheries.
[a] Figures from the Population Censuses of 1990, 2000 and 2010.

Land inequality measures also exhibit a non-linear pattern, decreasing in the first decade and then increasing to levels higher than in 1991. The Gini coefficient – the most commonly-used inequality indicator in the literature – is 0.606 in 2012, up from 0.59 in 1991 and 0.576 in 2002. Such levels are high for the ASEAN region but remains much below those recorded in Latin American countries (Guereña, 2016). The share of land occupied by different fractiles, shows a very similar pattern of decreasing inequality between 1991 and 2002 which is reversed between 2002 and 2012. At the end of the period, farms in the top percentile (decile) control almost 20% (50%) of the land, a share that has increased by more than 4 pp (3pp) since 2002. At the other end of the distribution, the 50% smallest farms occupy 12.3%, down from 13.74% in 2002.

To illustrate the changes in the landholding distribution, Figure 2 presents the temporal evolution in the number of farms and total farm area by land size category. Over time, the share of small farms (< 1ha) increases while the share of farms above 1 ha decreases. The share of land occupied by each category follows a similar pattern except that the decrease only starts after 2 ha. This may be due to the land reform which redistributed land to smallholders.

Figure 2: Farm size and land share distribution



Source: Philippine Statistics Authority - Census of Agriculture and Fisheries.

In the right tail of the distribution, the share of land occupied by farms above 20 ha remains stable between 2002 and 2012, despite a steady decrease in their numbers (from 0.38% of farms in 2002 to 0.21% in 2012), which indicates an increase in the size of very large farms. This is confirmed by the last graph which shows the share of land by fractile at the top of the distribution. While it remains relatively stable up to P99.99, the last 0.01% more than doubles its share between 2002 and 2012.

Finally, our measures of land ownership inequality exhibit a different pattern as they decrease over the period, probably as a result of the land reform. While the share of tenanted land decreases steadily over the two decades, the share of tenanted farms declines sharply between 1991 and 2002 and then remains stable around 25%.

3.1.3 Inequality decomposition and municipality-level land inequality

Since land is an immobile asset, it is expected that most of the inequality is to be found at the very local level. Intuitively, farmers need to live close to their farms either because they work in them or because they need to be able to monitor their workers. Therefore, it is not possible for large farmers to concentrate in specific areas in the same way that wealthy individuals live in the same neighborhoods. In the following, I compute the share of total inequality that can be attributed to within-municipality inequality. Since the Gini coefficient is not decomposable, the General Entropy (GE) index (also known as Theil's index) is used to address this question (see B for the technical details of the decomposition).

As expected, the results of this decompositions reported in Table 2 show that within-municipality inequality accounts for a very large share, around 80%, of total land inequality. The remaining between-municipality component comes from two sources. First, from differences in area and population density, which might reflect differences in soil fertility as small farms are only likely to be profitable in productive areas. Second, from farms occupying land across municipal boundaries. Indeed, if a farm is located on two municipalities, it will counted as one farm in the national measure but will be split into two in the municipal measure. Understanding national land inequality dynamics therefore require to understand how land distribution evolves at the local level.

Table 2: Inequality decomposition

		1991	2002	2012
Theil's T	Total	0.996	0.804	1.134
	Within municipality	0.785	0.686	0.953
		78.81%	85.32%	84.04%
	Within barangay			0.761
				67.11%
Theil's L	Total	0.672	0.636	0.727
	Within municipality	0.526	0.523	0.588
		78.27%	82.23%	80.88 %
	Within barangay			0.514
				70.70%

Source: Philippine Statistics Authority - Census of Agriculture and Fisheries.

We now turn to the description of municipality-level land distribution indicators[14]. Table 3 reports the descriptive statistics of municipality level land distribution[15]. Total land area and the number of farms follow similar a pattern on average as at the national level. The inequality measures, on the other hand, behave differently, as the Land Gini increases steadily over time, while it decreased at the national level during the first decade. More surprisingly, the average top 1% share decreases over time and the top 10% share remains remarkably stable. This suggests that the increase at the national level was driven by relatively larger municipalities[16].

[14] Maps of municipality-level Land Gini for the three waves of data are reported in Appendix C. Spatial correlation appears relatively limited, except for some regions characterized by strong land inequality such as the island of Negros in 1991 and central Mindanao in 2012. Temporal persistence, on the other hand, is high as unequal regions in 1991 tend to be more unequal in 2002 and 2012. The increase in land inequality over time is reflected by the darker colors in 2012.

[15] Since the main empirical analysis of this paper focuses on the difference between 2002 and 2012, I restrict the 2012 data to the barangays enumerated in 2002. This ensures that any difference we find is not explained by the sample composition. Municipalities with less than 50 ha of agricultural land are also dropped from the analysis, for two reasons. First, this restricts the sample to areas where farming is of some importance. Second, in areas with little agricultural land, an increase in landholding by one farm can have a strong effect on land inequality. This sample restriction therefore alleviates the issue of outliers driving our results. These restrictions are applied throughout the rest of the empirical analysis, unless otherwise stated.

[16] This is confirmed by the last two rows of the table, which present an additional inequality measure: the Lorenz Curve Dominance (LCD). If one distribution has a Lorenz curve that stochastically dominates the second, all synthetic inequality indicators agree that inequality is higher in the second distribution. If the curves intersect, the comparison is ambiguous and different parameter values can lead to diverging results. The LCD indicator is therefore a categorical

Table 3: Summary statistics of municipality level land distribution

	(1)		(2)		(3)	
	1991		2002		2012	
Variable	N	Mean/SD	N	Mean/SD	N	Mean/SD
Total land area	1426	5633.565	1554	5891.039	1546	4804.610
		(6280.106)		(6050.267)		(5548.008)
Nb of farms	1426	2574.292	1554	3035.497	1546	3020.781
		(2119.208)		(2479.916)		(2708.118)
Gini	1426	0.513	1554	0.518	1546	0.523
		(0.097)		(0.090)		(0.100)
Share top 1%	1426	0.137	1554	0.129	1546	0.127
		(0.119)		(0.097)		(0.112)
Share top 10%	1426	0.401	1554	0.402	1546	0.402
		(0.110)		(0.095)		(0.105)
Share bottom 50%	1426	0.168	1554	0.164	1546	0.160
		(0.047)		(0.045)		(0.052)
Share tenanted land	1426	0.356	1554	0.341	1546	0.314
		(0.161)		(0.159)		(0.162)
Share tenanted farms	1426	0.288	1554	0.248	1546	0.265
		(0.161)		(0.150)		(0.150)
LC dominance increase	1426		1473	0.298	1544	0.227
				(0.458)		(0.419)
LC dominance decrease	1426		1473	0.216	1544	0.212
				(0.412)		(0.409)

Source: Philippine Statistics Authority - Census of Agriculture and Fisheries.

3.2 Additional data sources

Aside from the agricultural data obtained from the CAF, several other data sources are exploited in this paper.

- Population at the municipality and the barangay level comes from the Census of Population (CP), available for the years 2000 and 2010.
- Philippine Standard Geographic Codes (PSGC) uniquely identify each administrative area in the country, down to the barangay level. They are used to match the different waves of CAF and CP data through time. Manual matching by names was carried out in order to increase the quality of the match[17].

variable equal to 1 if the Lorenz curve in time t-1 stochastically dominates that of time t (i.e. inequality increases). It is equal to 0 if both curves intersect (ambiguous result) and takes the value of -1 if t-1 is stochastically dominated by time t (inequality decreases). Over the period, inequality increases in more municipalities than it decreases, especially between 1991 and 2002. Given that the national Gini decreased during the same period, this indicates that this change was driven by larger municipalities. Between 2002 and 2012, the opposite is observed: the shares of municipalities where inequality increased and decreased were similar while national inequality measures increased, once again driven by larger municipalities.

[17] I am grateful to Andres Ignacio from ESSC for providing me his match between the PSGC 2000 and PSGC 2010.

- Administrative boundaries are obtained from the UN Office for the Coordination of Humanitarian Affairs (OCHA) and allows the matching between geo-coded data and the census data.

- Crop suitability measures come from the Global Agro-Ecological Zones (GAEZ) database from the FAO, which predicts yields for each crop based on soil, climate conditions and agricultural practices at a resolution of 10km per pixel. This measure will be further detailed in the section presenting the empirical strategy.

- Geophysical measures such as altitude and ruggedness are computed thanks to the Space Shuttle Radar Topography Mission (SRTM) digital elevation model, which has a pixel size of 90m.

- Night lights data come from the Defense Meteorological Program Operational Line-Scan System (DMSP-OLS), with a pixel size of 1km. Since this data is available as far back as 1992, it gives a good proxy of economic development ten years before our study period, therefore allowing to control for differential trends.

- Net Primary Productivity shows the difference between the carbon dioxide taken in by plants through photosynthesis and that released through respiration. It is available at a monthly frequency since 2000 from the NASA Earth Observatory (NEO) with a pixel size of 10km. Due to strong seasonal variation in the measure, I take the average over the three years surrounding the CAF data collection (2001-2003 for CAF 2002 and 2011-2013 for CAF 2012).

- Tree cover in 2000 and 2010 is obtained from the Hansen et al. (2013) global data which provides the tree cover share for each 30-m pixel.

- Terrorist activity data come from the Global Terrorism Database (GTD), a database created by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) from the University of Maryland that compiles newspaper reports of terrorist activities across the world.

4 Identification strategy

Genetically Engineered corn was introduced in the Philippines in 2003. The CAF 1991 was therefore conducted twelve years before this commercialization; the CAF 2002, one year before and the CAF 2012, ten years later. The empirical analysis therefore compares the last two waves of data, while using the first wave to control for historical differences that may be correlated with the treatment.

Since the data does not distinguish between different corn varieties, it is not possible to look at the direct impact of adoption on land use and distribution, regardless of the endogeneity of technology adoption. To overcome this issue, I use the empirical strategy developed by Bustos et al. (2016) in their paper on structural transformation in Brazil. This strategy exploits the fact that differences in soil and weather characteristics lead to differences in potential gain from adopting the technology, thereby creating exogenous cross-sectional variation in adoption and in treatment intensity. The measure of this exogenous potential gain from GE crop cultivation is obtained from the FAO GAEZ database, which predicts yields for each crop based on soil, climate conditions and agricultural practices. Crucially for our strategy, those agricultural practices include various degrees of input level intensity. The low level of inputs implies that "*the farming system is largely subsistence based. Production is based on the use of traditional cultivars (...), labour intensive techniques, and no application of nutrients, no use of chemicals for pest and disease control and minimum conservation measures*". The high level implies that "*[c]ommercial production is a management objective. Production is based on improved or high yielding varieties, is fully mechanized with low labour intensity and uses optimum applications of nutrients and chemical pest, disease and weed control*". The difference in potential yield between high and low levels of inputs therefore provides a measure of the profitability gain from GE corn cultivation. Importantly, this measure is only based on exogenous soil and weather characteristics and not on observed yields, which are endogenous to the adoption of the technology. Given that most of the corn cultivation in the Philippines is rain fed, we use the data under this water source regime.

This estimation strategy can be formalized with the following equation:

$$y_{it} = \delta_i + \delta_t + \beta A_{it} + \epsilon_{it}, \tag{1}$$

where y_{it} is an outcome variable that varies across municipality i at time t. δ_i and δ_t are respectively municipality and year fixed effects. A_{it} is the measure of potential corn yield, and takes the value under low level of inputs before 2003 and under high level of input after [18]. In the main specifications, the analysis is restricted to the years 2002 and 2012. In that case, the fixed effect equation is equivalent to the first difference model

$$\Delta y_i = \Delta\delta + \beta\Delta A_i + \gamma_1 X_i + \gamma_2 Z_{i,1991} + \Delta\epsilon_i \tag{2}$$

β, our coefficient of interest, reports how the outcome variable changes between two periods following an increase in potential yield due to the introduction of new agricultural technology. Estimates of β have a causal explanation provided that changes in potential yields are independently distributed from the outcome variable once we control for all time-invariant characteristics and common shocks. If areas that benefited more from the technology were on different trends from those who benefited less, this assumption would be violated and the estimates would be biased. To alleviate this concern, I include time-invariant geographical controls X_i and socio-economic indicators computed from the CAF 1991, $Z_{i,1991}$.

X_i include the log of municipal area and, in some specifications, elevation, ruggedness, longitude and

[18] The agricultural sector obviously did not change from being completely traditional to being fully mechanized with the introduction of GE corn seeds. In robustness check, I show that the results still hold when intermediate levels of inputs are used either in the pre- or in the post-adoption period.

latitude. Controlling for these last four variables is however problematic as they are used in the computation of the potential yield A_i. The interpretation of the coefficient β is therefore going to be different when they are included. On the other hand, excluding them may bias the estimates as they are correlated to other determinants of land inequality trends, such as market access or the occurrence of natural disasters. In robustness check, I therefore show that the results hold when each variable is added individually.

Trends in land inequality and technology adoption are likely to differ depending on baseline land scarcity. In frontier regions where new land can be cleared, we would expect lower agricultural productivity and different land market dynamics compared to places where all the land is already under cultivation. For this reason, $Z_{i,1991}$ includes the share of total municipal area dedicated to agriculture in 1991. It also includes the logarithm of night light intensity in 1992, which controls for a combination of initial population density and economic development.

Summary statistics of the corn potential yields, with different levels of input, are presented in Table 4. They are expressed in tons per hectare, with the last row presenting the difference between high and low levels of inputs. Moving from low to high level of inputs more than triples the potential yield, with some regions gaining as much as four times the average. These values are lower than the average actual yields given that they are computed over the entire country, including the areas not suitable for agriculture.

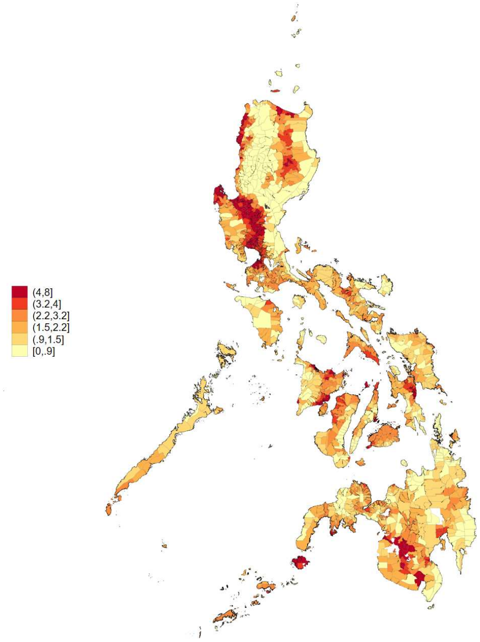
Table 4: Summary statistics of corn potential yield

	Mean	Std Dev	Min	Max
Low input level	0.703	0.420	0	2.116
High input level	2.312	1.432	0	9.805
High - Low	1.609	1.104	0	7.997

Source: FAO GAEZ

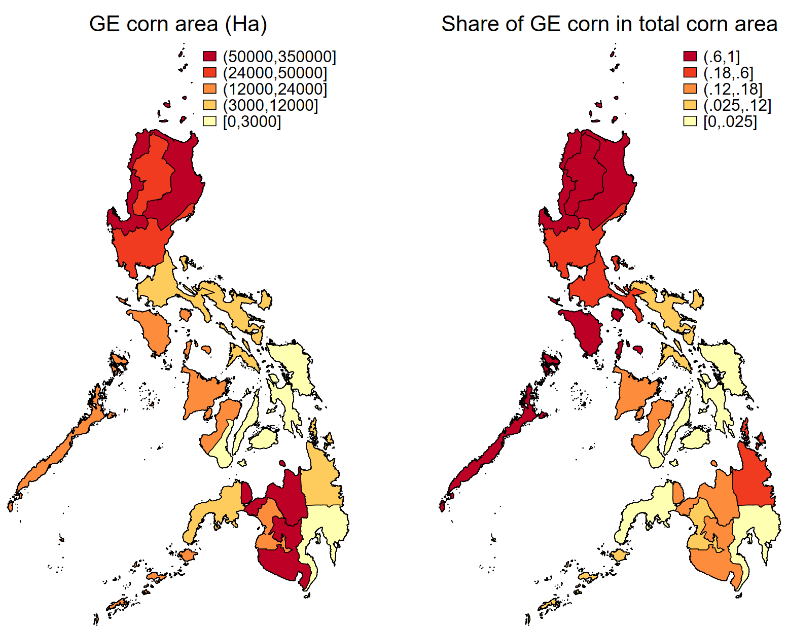
The geographical distribution of the potential gain in corn yield is presented in Figure 3. Potential yield gain also appears to be correlated with GE corn adoption, as presented in Figure 4. As previously explained, the agricultural census does not distinguish between different corn varieties. To the best of my knowledge, the most disaggregated data on GE corn adoption comes from the Department of Agriculture and is only available at the regional level for the years 2003-2009 and 2014. The maps use data from 2014 on the total area planted in GE corn and the share of total corn area planted in GE varieties. Places with high potential yield (Northern and Central Luzon, Southern Mindanao) correspond to areas with high GE penetration, especially in absolute area.

Figure 3: Geographical distribution of potential corn yield gain



Source: FAO-GAEZ.

Figure 4: Geographical distribution of GE corn cultivation in 2014



Source: Data provided by the Philippine Statistical Agency.

5 Results

5.1 Agricultural practices

The results of estimating Equation 2 on indicators of agricultural practices are presented in Table 5. The first two columns look at the importance of corn agriculture, measured as the difference in the log of corn area and the change in the share of agricultural land devoted to corn. Both measures are positively correlated with potential gain, indicating that, following GE corn introduction, corn cultivation increased in areas that benefited more from the technology. This brings credibility to the estimation strategy as farmers react differently to the technology depending on the soil and weather characteristics of their land.

Table 5: Productivity change and agricultural practices

VARIABLES	(1) Δ Corn area (Log)	(2) Δ Corn share	(3) Δ Ag area (Log)	(4) Δ Farm nb (Log)
Potential gain from GE corn	0.119***	0.013***	0.028**	-0.010
	(0.029)	(0.003)	(0.013)	(0.013)
Municipality area (Log)	-0.031	-0.021***	0.068***	0.022
	(0.041)	(0.004)	(0.018)	(0.018)
1991 Ag area (Share)	-0.430***	-0.092***	0.091	0.087
	(0.130)	(0.014)	(0.060)	(0.059)
1991 Night lights (Log)	-0.083***	-0.005**	-0.065***	-0.049***
	(0.027)	(0.002)	(0.012)	(0.012)
Observations	1,435	1,435	1,435	1,435
R-squared	0.019	0.071	0.042	0.028

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This increase in corn area appears to be – at least partly – driven by the change in agricultural area as this measure is positively correlated with the potential yield gain. This however does not necessarily imply agricultural land *expansion* in more affected municipalities as this effect is a relative one, comparing places more and less affected by the technology. As the general trend over the period is toward a contraction in agricultural land, it is possible that the positive effect corresponds to a smaller decrease in farm area. This relative increase in agricultural land is not driven by a relative increase in farm number as this variable is unaffected by the new technology (Column 4). Overall, a median increase in potential yield increases agricultural area by 5.1% and the share of corn by 2.4 percentage points or corn area by 21.6%.

5.2 Land inequality

It is a priori unclear how the increase in agricultural area affects land inequality as it depends on the place in land distribution occupied by the farms that expand their landholding. To address this question, Table 6 present the results from the same regression on measures of land inequality. The first two columns use the percentage point-change in landholding Gini as dependent variable and show that this measure is positively correlated with the profitability of the technology. When we control for municipal area and differential trends based on agricultural importance and economic development, the coefficient remains relatively stable but loses some significance. The same is true in the last two columns which use the land share of the top decile as dependent variable. Results with control variables imply that a median increase in potential yield leads to a 0.8-point increase in the Gini index and a 0.9-percentage point increase in the top 10% share.

Table 6: Productivity change and landholding inequality

	(1)	(2)	(3)	(4)
VARIABLES	Δ Gini		Δ Top 10%	
Potential gain from GE corn	0.526***	0.442**	0.591***	0.520**
	(0.191)	(0.205)	(0.213)	(0.233)
Municipality area (Log)		1.137***		1.331***
		(0.296)		(0.338)
1991 Ag area (Share)		3.902***		3.197***
		(0.894)		(1.002)
1991 Night lights (Log)		0.364**		0.468**
		(0.179)		(0.200)
Observations	1,521	1,435	1,521	1,435
R-squared	0.006	0.026	0.006	0.023

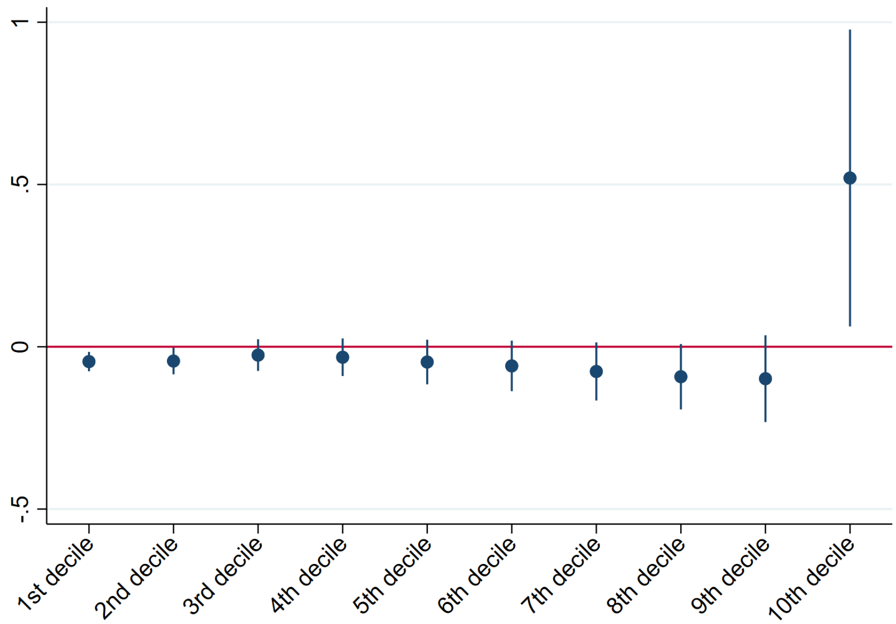
Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The impact of the new technology on the landholding distribution is presented in Figure 5, which replicates the last column of Table 6 using each decile land share as outcome variable. Apart from an increase in the top decile, results show that the change in inequality is also driven by a decrease in land share for the smallest 20% and the largest 50-80% farms, while the others remain relatively unaffected.

5.2.1 Land ownership inequality

Changes in landholding inequality can either be due to changes in land ownership inequality or to reallocation through the land rental market. Due to data constraints, it is however impossible to repeat the analysis using the same inequality measures for land ownership. Instead, we can look at the share of land that is not owned by the household cultivating it. Given that land ownership tends to be less equally distributed than landholding, an increase in that measure indicates an increase in land ownership inequality. Similarly, an increase in the share of tenanted farms also indicates more ownership inequality. Table 7 presents the results obtained by estimating Equation 2 using the two aforementioned land ownership measures as dependent variables. The share of tenanted land decreases in municipalities that benefited more from the technology, although this effect becomes insignificant

Figure 5: Impact of productivity change on land share for each decile



once we add the control variables. The share of tenanted farms, on the other hand, increases with the potential gain, and the effect becomes stronger with the controls. Overall this suggests that the increase in landholding inequality is reflected in the land ownership distribution as a smaller proportion of farms own a larger (or similar) share of the land. This may be driven by the land expansion in the last decile of the landholding distribution.

5.3 Mechanisms

Table 8 explores several potential mechanisms by adding variables measuring the change in agricultural practices, population and economic development. First, I control for the change in land share of crops in Column 2[19]. The increase in land devoted to corn – or the simultaneous change in any crop share – does not drive our result as the coefficient of potential gain becomes larger. This may be due to the fact that the data does not differentiate between GE and non-GE corn. Another mechanism is that of demographic and economic changes resulting from the increased productivity. For example, more productive areas may experience different rates of urban migration, thereby changing the pressure on the land. If productivity gains translate into income gains, this may also lead to the creation of non-agricultural businesses, with farming as a part-time occupation.

However, none of these mechanisms are supported by the data as the coefficient remains remarkably stable when we control for the log change of population, the change in rural population share and the

[19]Included crops are corn, rice, sugarcane, banana, coconut, other temporary crops and other permanent crops, with non-cultivated land as the omitted category

Table 7: Productivity change and land ownership inequality

	(1)	(2)	(3)	(4)
VARIABLES	Δ Tenanted land		Δ Tenanted farms	
Potential gain from GE corn	-0.663**	-0.539*	0.550*	0.469
	(0.285)	(0.317)	(0.317)	(0.354)
Municipality area (Log)		-1.394***		-2.645***
		(0.445)		(0.418)
1991 Ag area (Share)		-5.273***		-9.421***
		(1.496)		(1.483)
1991 Night lights (Log)		-0.252		-0.034
		(0.287)		(0.284)
Observations	1,521	1,435	1,521	1,435
R-squared	0.004	0.017	0.003	0.050

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

log change of night light intensity (Column 3). Finally, the effect of GE corn introduction on land inequality may be driven by other changes in the land distribution, such as the number of farms and the total land area. Controlling for the farm number does not affect the result, which was expected given that this measure was unaffected by the new technology as shown in the last column of Table 5. On the other hand, the coefficient of potential gain sharply decreases and becomes insignificant when we control for the change in total agricultural area. The increase in land inequality therefore appears to be more driven by a relative increase in farm area than by reallocation of land between farmers. Table D.1 in the Appendix shows that similar results are obtained when we use the top decile land share instead of the landholding Gini as dependent variable.

5.4 Heterogeneous effects

A common story in anti-GMO advocacy is that of predatory lending resulting in farmers taking on too much debt and eventually defaulting. Their lands are then confiscated by the moneylender or they are forced to sell them (Masipag, 2013). As a result, moneylenders or other better-off households are able to increase their landholding, resulting in an increase in land inequality[20]. The CAF data does not provide enough information to precisely test this story but can still give us some suggestive evidence. Indeed, the CAF 1991 asked farming households whether they contracted a credit (formal or informal) over the preceding year. Aggregated at the municipality level, this question gives us a measure of credit penetration 10 years before GE corn was introduced[21]. If such claims were true, we would expect to see a stronger effect in municipalities where credit availability is higher. The second column

[20]This claim is not contradicted by Figure 5 which shows little effect of GE corn at the bottom of the distribution. Indeed, if farmers sell their entire farm, they are removed from the land distribution.

[21]Note that the effect of financial development is a priori not clear. When it is inexistant, only a few wealthy farmers will have the opportunity to adopt the technology and reap its benefits, which should worsen inequality. A high level of credit availability therefore implies that more farmers have access to the technology and its higher yields. In this case, we would expect to see a low level of inequality in municipalities with better access to financial services.

Table 8: Landholding Gini and productivity change - Demographic and economic mechanisms

VARIABLES	(1)	(2)	(3)	(4)	(5)
Potential gain from GE corn	0.442**	0.504**	0.442**	0.448**	0.235
	(0.205)	(0.196)	(0.192)	(0.192)	(0.186)
Municipality area (Log)	1.137***	0.808***	0.867***	0.840***	0.520*
	(0.296)	(0.289)	(0.290)	(0.292)	(0.276)
1991 Ag area (Share)	3.902***	2.549***	2.476***	2.382***	2.336***
	(0.894)	(0.869)	(0.882)	(0.895)	(0.815)
1991 Night lights (Log)	0.364**	0.436**	0.506***	0.561***	0.631***
	(0.179)	(0.174)	(0.188)	(0.191)	(0.179)
Δ Population (Log)			-2.677	-2.646	-0.452
			(2.162)	(2.137)	(1.987)
Δ Rural pop (Share)			-1.153	-1.338	-6.580
			(8.979)	(8.884)	(8.142)
Δ Night light (Log)			0.825**	0.895**	0.588
			(0.417)	(0.416)	(0.364)
Δ Nb farms (Log)				0.954*	-5.915***
				(0.508)	(0.874)
Δ Farm area (Log)					8.593***
					(0.858)
Observations	1,435	1,435	1,424	1,424	1,424
R-squared	0.026	0.221	0.225	0.227	0.334
Crop share	NO	YES	YES	YES	YES

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

of Table 9 repeats the analysis of the Land Gini, controlling for the degree of credit penetration in 1991 and interacting it with our potential gain measure. None of the additional coefficients are significant, implying that credit may not be an important mechanism.

However, credit penetration is potentially correlated with other agricultural development measures, which may also play a role in our story. The CAF 1991 also asked farmers whether they were cultivating high-yield varieties (HYV) over the past year. Responses to this question are aggregated at the municipality level to obtain an indicator of the modernity of agricultural practices ten years before treatment. As Column 3 shows, the effect of potential gain on the Land Gini is highest in municipalities with low HYV use in 1991 and is equal to zero in areas where improved seeds were already widely adopted.

This result first suggests that our main result is driven by municipalities that were lagging behind in the modernization of their agriculture, and therefore where the potential for yield improvement was the

Table 9: Landholding Gini and productivity change - Historical cultivation practices

VARIABLES	(1)	(2)	(3)	(4)	(5)
Potential gain from GE corn	0.442**	0.338	1.017**	0.787*	0.841*
	(0.205)	(0.409)	(0.438)	(0.458)	(0.432)
Credit 1991		-0.339		-2.987*	-3.071*
		(1.457)		(1.743)	(1.717)
Pot. yield * Credit 1991		0.210		1.887***	1.580**
		(0.621)		(0.723)	(0.717)
HYV 1991			2.203	4.132**	2.606
			(1.528)	(1.844)	(1.811)
Pot. yield * HYV 1991			-1.155*	-2.459***	-2.233***
			(0.668)	(0.804)	(0.773)
Municipality area (Log)	1.137***	1.137***	1.108***	1.085***	0.757**
	(0.296)	(0.298)	(0.296)	(0.298)	(0.295)
1991 Ag area (Share)	3.902***	3.898***	3.776***	3.483***	2.755***
	(0.894)	(0.897)	(0.916)	(0.916)	(0.883)
1991 Night lights (Log)	0.364**	0.366**	0.359**	0.369**	0.707***
	(0.179)	(0.181)	(0.181)	(0.182)	(0.178)
Δ Farm area (Log)					5.551***
					(0.704)
Observations	1,435	1,435	1,435	1,435	1,435
R-squared	0.026	0.026	0.028	0.032	0.140

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

largest. Second, since credit and HYV are positively corelated, the results presented in Column 2 might be biased downwards (and those of Column 3 upwards). Indeed, when we allow for different trends depending on both credit and HYV penetration, we respectively find a positive and negative significant coefficient for the interaction term (Column 4). Moreover, this mechanism remains significant when controlling for the change in farm area (Column 5). Once again, using the land share of the top decile as dependent variable leads to similar conclusions (Table D.2 in the Appendix).

6 Robustness tests

6.1 Topo-geographical characteristics

Our empirical strategy relies on a measure of potential yield gain, which is computed using soil and weather characteristics. However, these characteristics may affect the trend in land inequality through other channels than land productivity. For example, elevation and ruggedness determine the availability of transport infrastructure and therefore input availability and market access. Similarly, extreme weather patterns affect the accumulation of physical capital, with consequences for the trend in economic development. On the one hand, omitting these variables from the regression, as has been the case so far, might therefore bias our estimates. On the other hand, if we control for them, the potential gain variable loses part of its substance and it is not clear how to interpret the coefficients.

To address this issue, I re-estimate the main regression for the landholding Gini, adding topo-geographical control variables and present the results in Table 10. In order to keep some informational value in the potential gain variable, the controls are added individually in each regression. Columns 2 and 3 control for average elevation and ruggedness index. In both cases, the point estimate becomes larger and more significant, indicating that, if anything, the omitted variable bias was pushing our coefficient downwards. Column 4 controls for longitude and latitude, which is strongly correlated with weather patterns, especially extreme weather since tropical cyclones hit the northern half of the country on a yearly basis while missing almost systematically the southern part. The inclusion of these variables does not impact our result. Finally, the last column assumes that trends in land inequality differ at the provincial level and therefore allows for province fixed effects. While the value of the coefficient does not change much, its significance decreases (p-value = 15.7%). These results remain valid when using the top decile land share instead of the landholding Gini (Table D.3 in the Appendix).

6.2 Placebo test

The results presented in this paper are causal provided that there is no differential trend in land inequality correlated with the potential yield gain once we control for municipal area, night lights and agricultural land share in 1991. One way to test this hypothesis is to run a placebo test comparing data from 1991 and 2002, i.e. before the introduction of GE corn. Results of this placebo test are presented in Table 11. Note that, contrary to what we have done so far, municipality-level measures of land inequality are not computed from the same set of barangays given the sampling method of the CAF 1991 and 2002. It is therefore impossible to rule out the fact that the results presented in this table are partly due to sampling differences.

When no controls are included, we find a weakly significant, negative, correlation between potential yield gain and the change in Gini index or in the top decile land share. This effect decreases sharply and becomes insignificant when we control for municipal area, agricultural land share and night light intensity. This implies that if there is any difference in trends between municipalities that benefited more from the technology and those that benefited less, this difference would bias our estimates downwards and the results presented in this paper are only a lower bound.

6.3 Spatial correlation

Given that soil and weather characteristics are not distributed randomly over the country, potential corn yield is likely to exhibit some level of spatial auto-correlation. Not taking this into account leads to an underestimation of standard errors, thereby increasing the probability of excluding the null hypothesis when we should not. For this reason, Table 12 reports the p-value obtained when re-estimating our

Table 10: Landholding Gini and productivity change - Topo-geographical controls

VARIABLES	(1)	(2)	(3)	(4)	(5)
Potential gain from GE corn	0.442**	0.785***	0.822**	0.607***	0.399
	(0.205)	(0.236)	(0.369)	(0.214)	(0.281)
Municipality area (Log)	1.137***	0.993***	1.078***	1.059***	-0.370
	(0.296)	(0.302)	(0.299)	(0.299)	(0.406)
1991 Ag area (Share)	3.902***	4.081***	4.153***	2.667***	1.654
	(0.894)	(0.887)	(0.897)	(0.958)	(1.342)
1991 Night lights (Log)	0.364**	0.348*	0.376**	0.403**	0.157
	(0.179)	(0.180)	(0.179)	(0.181)	(0.232)
Elevation		0.003**			
		(0.001)			
Ruggedness			0.027		
			(0.021)		
Longitude				0.367*	
				(0.198)	
Latitude				-0.049	
				(0.112)	
Observations	1,435	1,435	1,435	1,435	1,433
R-squared	0.026	0.033	0.027	0.032	0.188
Province FE	NO	NO	NO	NO	YES

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

main results with alternative clustering techniques. The first row shows the p-values obtained from the robust standard errors that we have used so far. The second and third rows the correction suggested by Conley (1999) using a 25-km and a 50-km radius and the last row when standard errors are clustered at the provincial level. When control variables are not included, the coefficients remain below the 5% threshold with the 25-km radius and below the 10% with the 50-km radius. When controls are included, p-values are larger but always remain below 15%. Provincial-level clustering yields standard errors somewhere between the two radius values.

6.4 Barangay-level analysis

So far, the empirical analysis as been based on the average potential yield gain computed over municipalities. However, due to the geographic characteristics of the country, the level of within-municipality heterogeneity in the Philippines tends to be high. For example, the median municipality area is equal to 119 sq km and the median elevation range (difference between highest and lowest altitude) is 543m, reflecting the hilliness of the country. Similarly, the within-municipality standard deviation in potential yield is equal to 0.65 on average, which correspond to half of the standard deviation computed

Table 11: Placebo test using 1991 and 2002 data

VARIABLES	(1) Δ Gini	(2)	(3) Δ Top 10%	(4)
Potential gain from GE corn	-0.290*	0.025	-0.343*	-0.129
	(0.175)	(0.195)	(0.191)	(0.226)
Municipality area (Log)		-0.937***		-0.991***
		(0.294)		(0.340)
1991 Ag area (Share)		-7.159***		-4.781***
		(1.382)		(1.697)
1991 Night lights (Log)		-0.423*		-0.484**
		(0.217)		(0.238)
Observations	1,353	1,344	1,353	1,344
R-squared	0.002	0.036	0.002	0.019

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: Spatial correlation correction

VARIABLES		(1) Δ Gini	(2)	(3) Δ Top 10%	(4)
Potential gain from GE corn		0.526	0.442	0.591	0.520
	Robust SE	[0.006]	[0.031]	[0.006]	[0.026]
	Conley 25-km radius	[0.026]	[0.077]	[0.035]	[0.089]
	Conley 50-km radius	[0.053]	[0.115]	[0.076]	[0.136]
	Province cluster	[0.044]	[0.106]	[0.056]	[0.096]
Observations		1,521	1,519	1,521	1,519
R-squared		0.006	0.026	0.006	0.025
Controls		NO	YES	NO	YES

Source: Census of Agriculture and Fisheries 2002 and 2012
P-values between brackets.

between municipalities. Given this heterogeneity, we cannot be sure that increases in land inequality are actually observed in areas that became more productive. For example, it may be that inequality increased in areas close to those where productivity increased. While such spill-over effects may not invalidate our results, it may be important to understand them from a policy perspective.

To address this issue, I repeat the analysis using barangay-level data and present the results in Table 13. Before interpreting the results, it is important to remind the differences between barangay- and municipality-level data. First, the plot physical location is only available at the municipality level. Barangay land inequality measures are therefore computed on the total land cultivated by people living in the barangay, not on the land located within its boundaries. While both sets are the same in most cases, large farms straddling administrative boundaries and absentee landlords will create a wedge between them. It is therefore possible to have a value of agricultural area larger than the total barangay area, which was not the case in the municipality data as we used the physical location of the plot. Second, due to the sampling method used in the successive rounds of the CAF, the number of observations will vary depending on which variables we include in the analysis. More specifically, when controlling for 1991 variables, the observation number will strongly decline as we only use the balanced sample over the three waves[22]. Third, while municipalities with less than 50 ha of agricultural land were excluded from the analysis, this threshold is decreased to 10 ha for barangays. Once again, this avoids taking into account areas where farming is a marginal activity and where small changes in the land distribution can have a large impact on inequality measures. Finally, while most municipalities comprise both urban and rural areas, barangays usually fall in only one of those categories. Given that agricultural land inequality is not a relevant topic in urban areas, it makes sense to restrict the sample to rural barangays only .

Results from Table 13 are remarkably similar to those from Table 6, especially when we restrict the analysis to rural barangays (Columns 3 and 6). In those barangays, a median increase in potential yield leads to a 1.5-point increase in Gini coefficient and a 0.7-percentage point increase in the top 10% land share. The results obtained at the municipality level are therefore unlikely to be an artefact of aggregation.

Table 13: Barangay-level analysis

	(1)	(2)	(3)	(4)	(5)	(6)
		Δ Gini			Δ Top 10%	
VARIABLES	Full 2002-12	Full 1991-02-12	Rural barangays	Full 2002-12	Full 1991-02-12	Rural barangays
Potential gain from GE corn	0.576***	0.649***	0.810***	0.367***	0.215	0.383**
	(0.121)	(0.174)	(0.186)	(0.109)	(0.162)	(0.170)
Barangay area (Log)		0.368*	0.491**		-0.265	0.012
		(0.215)	(0.236)		(0.212)	(0.226)
1991 Ag area (Share)		-0.018	-0.026**		0.007	0.009
		(0.016)	(0.012)		(0.006)	(0.006)
1991 Night lights (Log)		0.088	1.140		-0.466	0.752
		(0.903)	(1.163)		(0.744)	(0.969)
Observations	11,967	6,799	5,439	11,967	6,799	5,439
R-squared	0.004	0.005	0.009	0.002	0.002	0.002

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors clustered at the municipality-level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

7 Land inequality and socio-economic outcomes

Results presented in this paper document an increase in landholding inequality following the introduction of GE corn in the Philippines. Since land inequality has been shown to have adverse effect on welfare and economic development, the question of the net effect of the technology needs to be addressed. In other words, is the increased inequality a small price to pay given the gain in agricultural productivity? To investigate this question, the present section focuses on three outcomes: (i)

[22] See Appendix A.5 for the details regarding the sampling structure and the weights recomputation.

agricultural productivity, as measured by the net primary productivity, a remote-sensing indicator; (ii) night lights intensity, a measure which was used as a control variable in the previous analysis and (iii) terrorist activity. Unfortunately, I am not able to show any causal evidence as the potential yield measure cannot be used as an instrument for land inequality due to an obvious violation of the exclusion restriction. Results in this section are therefore purely correlational.

7.1 Agricultural productivity

First, the most direct impact of improvement in agricultural technology should be on agricultural productivity, which is proxied by the net primary productivity (NPP) given that the CAF does not provide agricultural output information. NPP is a satellite-based indicator measuring the difference between the carbon dioxide taken by plants through photosynthesis and the carbon dioxide emitted through respiration. It is therefore the flow of carbon stocked in plants over a given period and is used as a proxy for vegetation growth, crop yield, forest production etc. Given its high seasonal variation, I take the average measure over the three years around the CAF data: 2001-2003 and 2011-2013.

Table 14 presents the results of estimating our first-difference equation between 2002 and 2012 using the change in NPP as dependent variable. In simple correlation, municipalities that experienced an increase in NPP became more unequal and benefited more from the new technology. When both landholding Gini and potential gain are included in the regression, the point estimates remain very stable, indicating that the positive correlation between land inequality and agricultural productivity was not driven by the gain in potential yield. The size of the effect is however small as a one-standard deviation in landholding Gini (potential yield) is associated with a 0.1(0.05)-standard deviation in NPP. When we control for the change in crops and tree cover, both estimates strongly decrease and lose their significance (the Gini remains weakly significant with a p-value of 11.1%). Adding additional controls for the change in agricultural land, population and night light intensity increases the coefficients, especially that of the Gini index, which regains its significance. Although correlational, these results do not support the idea that landholding inequality is detrimental to agricultural productivity.

7.2 Night light intensity

A similar conclusion can be drawn from the Table **??**, which uses the log-change in night light intensity as dependent variable. Both landholding inequality and potential yield are associated with an increase in intensity and these correlations are robust to controlling for changes in demographic characteristics and in the importance of the agricultural sector. The implied effect is again very small, as a one-standard deviation change in Gini and potential yield respectively increase the night light intensity by 4.9% and 12.6% of a standard deviation.

Overall, these results do not provide evidence supporting the idea that the worsening of land inequality lead to adverse outcomes in terms of productivity and economic development. However, a lot of caution is needed when interpreting them due to the clear issue of reverse causality and the lack of exogenous

Table 14: Δ Net Primary Productivity

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Gini	0.135***		0.129***	0.081*	0.079	0.125**	0.121**
	(0.045)		(0.045)	(0.049)	(0.049)	(0.050)	(0.050)
Potential gain from GE corn		0.608**	0.540**		0.163		0.360
		(0.250)	(0.251)		(0.313)		(0.314)
Municipality area (Log)				0.274	0.347	0.325	0.488
				(0.437)	(0.466)	(0.434)	(0.462)
Δ Tree cover (Share)				0.288***	0.272**	0.296***	0.262**
				(0.097)	(0.107)	(0.098)	(0.107)
Δ Nb farms (Log)						-1.160	-1.105
						(1.086)	(1.088)
Δ Farm area (Log)						-0.940	-0.978
						(1.149)	(1.152)
Δ Population (Log)						-0.115	-0.544
						(3.415)	(3.448)
Δ Rural pop (Share)						1.337	1.347
						(17.202)	(17.323)
Δ Night light (Log)						-2.236***	-2.316***
						(0.594)	(0.600)
Observations	1,521	1,521	1,521	1,519	1,519	1,507	1,507
R-squared	0.008	0.003	0.010	0.055	0.055	0.070	0.071
Crop controls	NO	NO	NO	YES	YES	YES	YES

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

variation in land inequality.

7.3 Terrorist activity

Since the beginning of the 21st century, the Philippines have been faced with an increase in terrorist activities, perpetrated by left-wing guerilla and islamist insurgency groups. Figure 5 reports the number of attacks, deadly attacks and casualties reported each year in the Global Terrorism Database (GTD). Starting around 2005, the number of attacks, both lethal and non-lethal increase sharply while the number of casualties starts increasing around 2010 . The geographical distribution of the attacks is reported in Appendix E. Most of the events occur on the island of Mindanao, while the median number of attacks and of casualties at the provincial level is 17 over the period 1991 – 2018.

While part of this increase can be attributed to geopolitical events, such as the rise of islamist terrorism, some scholars have cited the unequal distribution on assets between ethnic groups, especially in the South of the country (McDoom et al., 2019). In order to test the correlation between land inequality and terrorist activity, I use the data provided by the GTD data aggregated at the province-year

Table 15: Δ Night Light Intensity (Log)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Gini	0.004**		0.004*	0.005**	0.004**	0.004*	0.003*
	(0.002)		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Potential gain from GE corn		0.071***	0.069***		0.061***		0.058***
		(0.012)	(0.012)		(0.013)		(0.013)
Municipality area (Log)				-0.051***	-0.018	-0.048***	-0.017
				(0.016)	(0.018)	(0.016)	(0.018)
Δ Population (Log)				0.498***	0.415***	0.492***	0.410***
				(0.144)	(0.141)	(0.143)	(0.141)
Δ Rural pop (Share)				2.051***	1.960***	2.023***	1.943***
				(0.612)	(0.607)	(0.613)	(0.607)
Δ Nb farms (Log)						-0.159***	-0.141***
						(0.043)	(0.044)
Δ Farm area (Log)						0.065	0.051
						(0.045)	(0.045)
Observations	1,520	1,520	1,520	1,507	1,507	1,507	1,507
R-squared	0.004	0.024	0.027	0.025	0.040	0.034	0.048

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

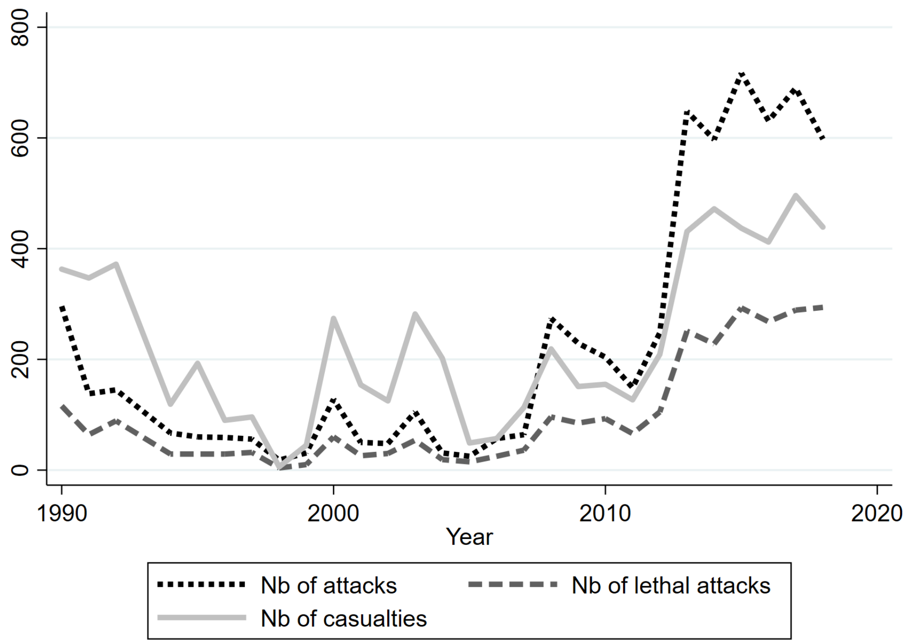
level, given the relatively rare occurrence of terrorist attack at the municipality level. While previous regressions in this paper were always comparing two data points ten years apart per municipality, the model estimated here is different:

$$y_{jt} = \delta_j + \delta_t + \beta_1 Gini_{jt} + \beta_2 \Delta A_j * year_t + \gamma X_{jt} + \epsilon_{it}, \tag{3}$$

Where y_{jt} is the number of terrorist attacks or of casualties in province j in year t and ΔA_j is the gain in potential corn yield, which is interacted with a time trend in order to control for trends difference based on agricultural productivity. The land Gini is recomputed taking into account the province where plots are located. Linear change is assumed for all time-varying variables (Gini, log of farm area, farm number and night lights) in order to fill the blanks in the panel data. Finally, province fixed effects and year fixed effects are included to remove any unobservable time-invariant and aggregate shocks, such as geographical characteristics, geopolitical situation and methodological changes in terrorism data collection.

Results from Columns 1 and 5 of Table 16 show that, on average over the period 1991-2018, a 1-point increase in the landholding Gini increases the number of attacks by 0.19 and the number of casualties by 0.12 every year. Municipalities that benefited more from the introduction of GE corn appear to experience a stronger increase in terrorist activity over time, which is not due to changes in land inequality as the point estimate of the Gini index increases slightly when we control for potential yield.

Figure 6: Temporal variation in terrorist activity at the national level



The effect of land inequality on terrorist activity increases becomes even stronger when we control for changes in the structure of the agricultural sector and night light intensity. Finally, Columns 4 and 8 restrict the sample between 2002 and 2012, thereby avoiding issues related to the comparability between CAF 1991 and 2002 samples and to the extrapolation between 2012 and 2018. Such a restriction also allows us to control for demographic variables which are not available prior to 2000. The effect of land inequality on the number of attacks decreases but remains significant while it loses its significance on the number of casualties. This loss of significance appears to be mainly driven by the exclusion of the years 2013-2018.

8 Concluding remarks

This paper identifies the introduction of genetically engineered corn seeds as an important factor explaining the evolution of land inequality in the Philippines during the first decade of the 21st century. Our results show that municipalities that benefited more from this technology experienced an increase in landholding Gini and in the share of land occupied by the farms in the top decile. The magnitude of the coefficients implies that without the technology, both measures would have decreased over the decade, whereas the observed Gini increased and the top decile share remained constant. This increase in landholding inequality is accompanied by an increase in land ownership inequality as the introduction of GE corn decreases the share of land under tenancy status without reducing the share of tenanted farms. A similar proportion of farmers therefore own an increasing proportion of land, thus worsening land ownership inequality.

Table 16: Terrorist attacks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Nb of attacks				Nb of casualties		
VARIABLES	1991-2018			2002-2012	1991-2018			2002-2012
Gini	0.186***	0.220***	0.440***	0.211**	0.124***	0.154**	0.271***	0.087
	(0.061)	(0.077)	(0.151)	(0.094)	(0.046)	(0.059)	(0.088)	(0.172)
Potential gain from GE corn * Year		0.109*	0.163**	0.138***		0.099**	0.127***	-0.164
		(0.056)	(0.065)	(0.047)		(0.039)	(0.043)	(0.182)
Farm area (Log)			-9.354**	-5.112*			-5.029*	4.093
			(4.523)	(3.043)			(2.894)	(5.398)
Nb farms (Log)			9.270**	4.352			4.925*	-8.066
			(4.328)	(2.643)			(2.821)	(5.635)
Night Light (Log)			-1.086**	-2.895***			-0.569**	-2.194
			(0.463)	(0.541)			(0.286)	(1.630)
Population (Log)				20.900***				31.700**
				(4.867)				(15.848)
Rural pop (Share)				30.268**				-4.851
				(12.820)				(32.078)
Observations	2,236	2,236	2,236	820	2,236	2,236	2,236	820
R-squared	0.458	0.470	0.496	0.574	0.299	0.309	0.315	0.260
Province FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Source: Census of Agriculture and Fisheries 2002 and 2012 and Global Terrorism Database
Robust standard errors clustered at the provincial level in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Several mechanisms and heterogeneous effects have been identified. First, the increase in land inequality appears to be driven by the relative increase in agricultural land in municipalities that were more affected. This relative increase - compared to less affected area - does not necessarily imply an expansion of agricultural land and the environmental impact of the technology is left for future research. Second, the effect is stronger in places where agricultural credit transactions were widespread and improved seeds were less used in 1991.

These results do not take into account the implementation of the CARP land reform, which took place over the entire study period. This is due to a complete lack of data regarding the amount of land redistributed at a disaggregated level. Given the high level of redistribution reported by the government, this may pose a threat to the validity of our results if landlords' opposition to the process was stronger in regions that benefited more from the new technology. However, given that the CARP started in the 90s, landlords would have needed to anticipate the arrival of the technology in order to keep their land until 2002. If this was the case, we would observe a similar effect between 1991 and 2002, which is not the case as reported in Table 11. Such a political economy explanation is therefore unlikely to be driving our results. Moreover, the actual amount of land redistributed by the policy remains largely unknown given that official statistics appear unrealistically high.

One of the main limitation of the paper is that it lacks agricultural information on input and output and is therefore unable to link the change in inequality with changes in the agricultural production function. A priori, given that seeds and other inputs can easily be divided, GE corn technology appears to be scale neutral. There are, however, two reasons to believe this may not be entirely true. First, large farmers can buy their inputs in bulk and pay a lower price on them. Second, switching to the new technology entails a higher level of risk and poor farmers are less able to insure against it. Indeed, GE corn cultivation offers higher yields than alternative varieties thanks to its better weed and pest management, which increases the gross return on land, as more output can be harvested from a given area. At the same time, input costs also increase as seeds are more expensive and herbicide and fertilizer are used more intensively . These higher input costs imply large potential losses in case of crop failure, which increase the riskiness of agricultural production. In a country exposed to many natural hazards like the Philippines (tropical cyclones, drought, flooding etc.), the probability of an adverse event destroying the harvest is not negligible. This is especially the case for smallholder farmers, who have limited options to insure against such shocks. As a result, large farmers who have easier access to financial institutions and alternative income sources are more able to insure against the increase in risk and therefore to reap the benefits from the new technology. In addition, the labor-saving characteristics of GE seeds favor the capital-rich farmers, thereby increasing inequality.

Finally, although this paper shows that stories reported by anti-GMO activists are supported by the data, it is not meant to present any sort of welfare evaluation of the new technology. While a higher level of land inequality is associated with a higher occurrence of terrorist activity, it is also positively correlated with agricultural productivity and economic development, measured by satellite imagery. If the increased inequality has any welfare costs – which is not entirely supported by the data - , they are unlikely to outweigh the large benefits reported elsewhere on farm profits and household income.

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Appendix A Data cleaning details

A.1 Farm definition

The definition of a farm varies between the census waves. In 1991 and 2002, enumeration was limited to farms satisfying one of two conditions: (i) using at least 1000 square meters to raise crops, livestock or poultry and (ii) raising at least 20 heads of livestock or 100 heads of poultry. In 2012, however, this rule was lifted and any agricultural operation, regardless of land or herd size, was enumerated. Moreover, the rule does not appear to have been properly followed in 1991 as over one million farms report an area below 0.1 ha compared to only 8,355 in 2002. To make sure that temporal variations we find in the land distribution are not the result of changing farm definitions, farms with a total land area of less than 0.1 ha are excluded from the data. This implies dropping around 820,000 households in 2012. Through this restriction, we also make sure that the households considered devote a significant amount of resources to their farming activity, and we do not take into account all those who only tend a small plot of vegetables for their own consumption.

A.2 Use of PSGC

Tracking geographical units through time can be challenging if administrative boundaries change. The CAF raw data identifies the barangays (and the municipalities they are part of) using Philippine Standard Geographic Codes (PSGC). As administrative boundaries change, these codes are regularly updated, on average every two years. Unfortunately, the CAF documentation does not state clearly which version of the PSGC is used for each wave. In addition, the Philippine Statistics Authority was not able to provide a list of codes prior to 1998. I therefore use the version of PSGC that offers the highest number of matches, i.e. PSGC 1998 for the CAF 1991, the PSGC 2002 for the CAF 2002 and the PSGC 2018 for the CAF 2012. I was however unable to link 54 municipalities from the CAF 1991 to the rest of the data (representing 4.7% of the total agricultural area). Similarly, 3 and 1 municipalities had to be dropped from the CAF 2002 and CAF 2012 respectively.

To match municipalities across time, I use the PSGC 2002 version in order to minimize the distance with the other two. When municipalities merge or split between waves, I always use the larger entity for the analysis. Details of the PSGC matches are available upon request.

A.3 Crop area

In 1991 and 2002, the area planted in each crop is collected, along with the number of times that crop was planted. In 2012, however, we only know which crops were planted in each growing season. When several crops are cultivated on the same plot, we therefore do not know the area allocated to each one. In order to have consistent measures between years, I assume that when corn, rice or sugarcane are cultivated, they are planted on the entire plot. Given that they are rarely intercropped, this only leads to a slight overestimation of their prevalence. In addition, each crop is counted once, regardless of how many times it was harvested during the year. If a farmer grows rice during the wet season and corn during the dry season, his farm is included in the rice area as well as in the corn area. This implies that when we add the shares of land devoted to each crop, the result is likely to exceed one. Double counting of crops cultivated twice a year would lead to a stronger overestimation of their presence given that permanent crops such as coconut or banana are only counted once. Moreover, this measure is only used as a control variable in some regressions and the mismeasurement is unlikely to invalidate our main results.

For permanent crops such as coconut and banana, their dedicated area is very poorly reported and often missing. As many households own only a couple of trees, and they are much more likely to be intercropped, we would largely overestimate their presence by assuming that they cover the entire plot. The number of trees is however reported more reliably. I therefore use this information to recompute planted area by taking into account planting distance recommended by the Philippine Department of Agriculture. More specifically, I take planting densities of 123 plants/ha for coconut and 500 for banana (the median density in the 1991 data which contains both area and number of plants). In addition, the planted area is replaced by the plot area whenever it was larger.

A.4 Identification variables in CAF 2012

Respondents identification in the CAF 1991 and 2002 data are coherent and appear reliable, in the sense that it is possible to merge the different datasets with very limited loss of observations (only 20 unmatched plots in 1991 and less than 0.1% in 2002).

In the 2012 data, however, more cleaning is necessary in order to correclty match the different datasets. This is especially the case for the dataset containing plot-level tenure and use information. These variables are key to creating the land ownership inequality indicators used presented in Table 7. Agricultural operators are identified thanks to a series of ten identification variables (region, province, municipality, barangay, enumeration area, segment number, building serial number, housing unit serial number, household serial number and operator line). Manual inspection of those variables revealed that the last character of each entry was actually the first character of the following variable. For example, the farms located in the province of Abra report being in the region number 40 and the province number 10, while this province has the number 1 according to the PSGC. The same applies for all the subsequent identification variables. Correcting for this allows the matching of 98% of the observations. Removing the last digit of the household serial number to the unmatched variables increases the share of matched observations.

In addition to this problem with the id variables, the plotsizes reported in this dataset are rounded, for a reason that the PSA is not able to explain. As a result, 48% of the plots have a value of 0ha, which is problematic when computing land inequality indicators. This problem is solved using two methods. First, when the plots have a match in another dataset (for example, containing crop information), the plotsize is taken from there. This allows me to confirm that the problematic values were indeed rounded. Second, for plots that cannot be matched, for example because they are left fallow or contain pasture land, the rounded value is kept and the 0 values are replaced by 0.1 ha, which is the average size of the matched plots that reported this value.

A.5 Sampling and weights recomputation

The sampling procedures for CAF 1991 and 2002 were the following:

1. Four provinces were fully enumerated (Laguna, Isabela, Bukidnon and Batanes). The province of Marinduque was also fully enumerated in 1991 only.
2. In the remaining provinces, the barangay with the largest farm area according to the previous census was enumerated with certainty.
3. In 1991, 50% of the remaining barangays were enumerated.
4. In 2002, the remaining barangays were divided into two groups: those sampled in 1991 and the others. 25% of each stratum was selected.

Comparing the last two waves is straighforward as we only keep data from the barangays surveyed in 2002 and use their weight on both waves.

When combining all three waves, or when comparing the 1991 and 2002 data, we need to take the sampling procedure into account in order to recompute the weights. Indeed, weights can change between census wave and the probability of being part of the full balanced panel depends on the weights in both waves. More specifically, we should not increase the weight given to certainty barangays since they were not randomly selected and therefore only represent themselves. The recomputed weight is therefore the average of the initial weights corrected by a factor γ_{ijt}:

$$w_{ij} = \frac{1}{2}\left(w_{ij91}\gamma_{ij91} + w_{ij02}\gamma_{ij02}\right),$$

with the correction factor γ_{ijt} equal to 1 for the certainty barangays and to $\frac{N_{j91}}{\Sigma_i w_{ij91}}$ otherwise, where N_{jt} corresponds to the number of barangays enumerated in municipality j in year t.

Appendix B Inequality decomposition

The general formula of GE measures is given by

$$GE(\alpha) = \frac{1}{\alpha(\alpha-1)}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i}{\bar{x}}\right)^{\alpha} - 1\right],$$

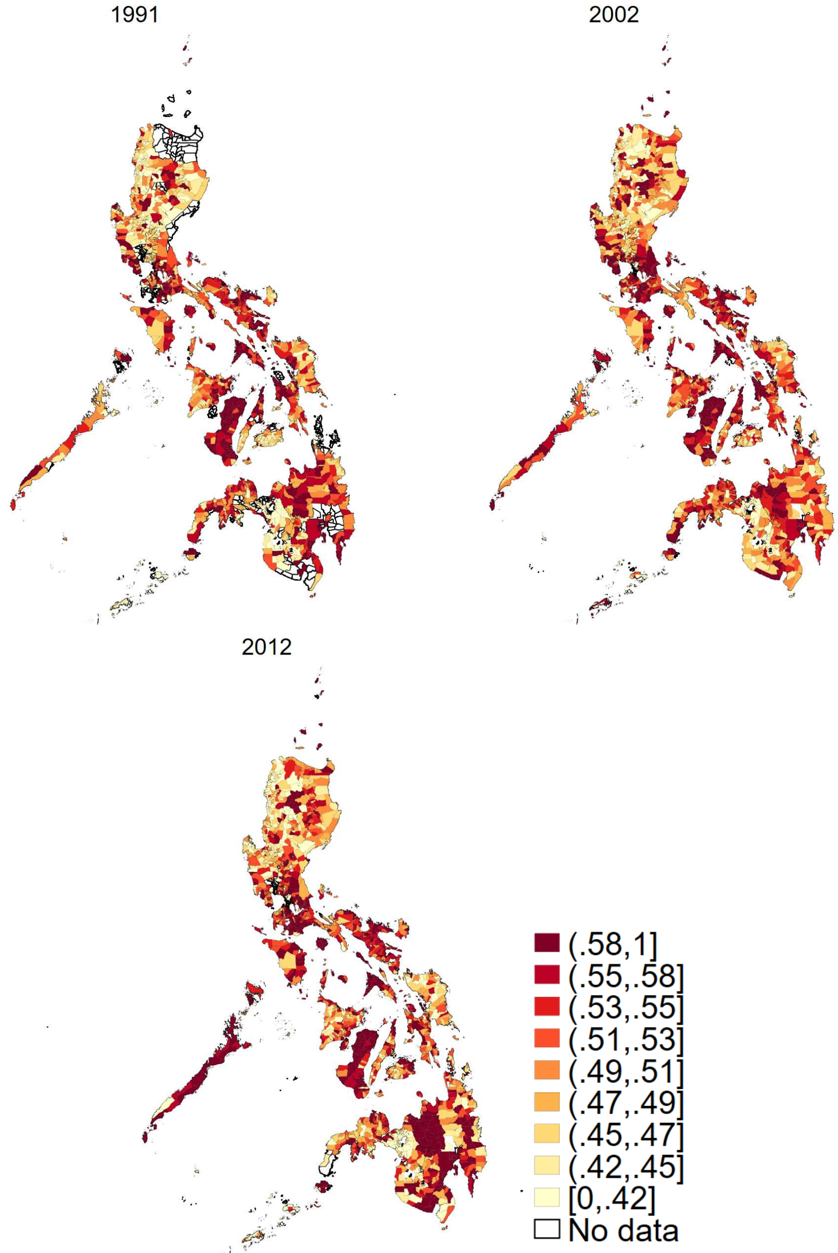
where x_i is the landholding size and $\bar{x}$ the mean farm size. The parameter α represents the weight given to land size differences along the farm size distribution, a low value giving more weight to the left tail of the distribution while a high value giving more weight to the right tail. The two most used values are 0 and 1, respectively giving Theil's L and Theil's T indices. These indicators can then be decomposed into two additive components, measuring between-municipality and within-municipality inequality. For Theil's T, this first decomposition is given by

$$\begin{aligned} T &= \frac{1}{N}\sum_{i=1}^{N}\frac{x_i}{\bar{x}} ln\left(\frac{x_i}{\bar{x}}\right) \\ &= \sum_{i=1}^{N}\frac{x_i}{X} ln\left(\frac{x_i N}{X}\right) \\ &= \sum_{j}\left(\frac{X_j}{X}\right)T_j + \sum_{j}\left(\frac{X_j}{X}\right) ln\left(\frac{X_j/X}{N_j/N}\right), \end{aligned}$$

where municipalities are indexed by j and T_j is the value of Theil's T index computed for municipality j[23]. It is also possible to decompose this measure along more than one level, provided that each level is nested within the other. This analysis is only possible for 2012 as it requires information on the full census of barangays. Following Akita (2003), I therefore decompose national inequality into three components: between municipality, between barangay and within barangay and report the results in Table 2.

[23] Theil's L index decomposes similarly, using the number of farms N as weights. For more information, see Haughton and Khandker (2009).

Appendix C Spatial distribution of landholding Gini



Source: Philippine Statistics Authority - Census of Agriculture and Fisheries.

Appendix D Supplementary regressions

Table D.1: Top decile share and productivity change - Demographic and economic mechanisms

VARIABLES	(1)	(2)	(3)	(4)	(5)
Potential gain from GE corn	0.520**	0.639***	0.518**	0.511**	0.269
	(0.233)	(0.215)	(0.205)	(0.205)	(0.196)
Municipality area (Log)	1.331***	0.931***	0.923***	0.958***	0.593*
	(0.338)	(0.336)	(0.332)	(0.332)	(0.307)
1991 Ag area (Share)	3.197***	1.530	1.555	1.675*	1.623*
	(1.002)	(0.992)	(1.005)	(1.011)	(0.901)
1991 Night lights (Log)	0.468**	0.546***	0.561***	0.490**	0.570***
	(0.200)	(0.186)	(0.196)	(0.203)	(0.194)
Δ Population (Log)			0.577	0.538	3.046
			(2.381)	(2.409)	(2.282)
Δ Rural pop (Share)			-2.395	-2.159	-8.149
			(8.557)	(8.639)	(7.668)
Δ Night light (Log)			1.061**	0.972**	0.621*
			(0.432)	(0.428)	(0.365)
Δ Nb farms (Log)				-1.218**	-9.068***
				(0.573)	(1.027)
Δ Farm area (Log)					9.819***
					(1.014)
Observations	1,435	1,435	1,424	1,424	1,424
R-squared	0.023	0.246	0.249	0.253	0.367
Crop share	NO	YES	YES	YES	YES

Source: Census of Agriculture and Fisheries 2002 and 2012

Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D.2: Top decile share and productivity change - Historical cultivation practices

VARIABLES	(1)	(2)	(3)	(4)	(5)
Potential gain from GE corn	0.520**	0.910*	1.620***	1.461***	1.508***
	(0.233)	(0.496)	(0.531)	(0.558)	(0.547)
Credit 1991		0.365		-1.941	-2.014
		(1.535)		(1.726)	(1.739)
Pot. yield * Credit 1991		-0.661		1.307*	1.041
		(0.710)		(0.752)	(0.764)
HYV 1991			2.142	3.412*	2.092
			(1.611)	(1.860)	(1.863)
Pot. yield * HYV 1991			-1.894**	-2.804***	-2.608***
			(0.770)	(0.875)	(0.859)
Municipality area (Log)	1.331***	1.361***	1.307***	1.286***	1.003***
	(0.338)	(0.343)	(0.339)	(0.342)	(0.347)
1991 Ag area (Share)	3.197***	3.178***	2.686***	2.472**	1.842*
	(1.002)	(1.008)	(1.030)	(1.027)	(1.005)
1991 Night lights (Log)	0.468**	0.451**	0.445**	0.453**	0.746***
	(0.200)	(0.201)	(0.201)	(0.201)	(0.202)
Δ Farm area (Log)					4.800***
					(0.918)
Observations	1,435	1,435	1,435	1,435	1,435
R-squared	0.023	0.024	0.031	0.033	0.097

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table D.3: Top decile share and productivity change - Topo-geographical controls

VARIABLES	(1)	(2)	(3)	(4)	(5)
Potential gain from GE corn	0.520**	0.925***	0.901**	0.787***	0.357
	(0.233)	(0.265)	(0.400)	(0.244)	(0.311)
Municipality area (Log)	1.331***	1.161***	1.272***	1.143***	-0.576
	(0.338)	(0.341)	(0.343)	(0.334)	(0.464)
1991 Ag area (Share)	3.197***	3.408***	3.449***	0.735	0.208
	(1.002)	(0.996)	(1.004)	(1.052)	(1.492)
1991 Night lights (Log)	0.468**	0.450**	0.481**	0.520***	0.232
	(0.200)	(0.201)	(0.200)	(0.201)	(0.261)
Elevation		0.004***			
		(0.001)			
Ruggedness			0.027		
			(0.022)		
Longitude				0.352*	
				(0.198)	
Latitude				-0.250**	
				(0.115)	
Observations	1,435	1,435	1,435	1,435	1,433
R-squared	0.023	0.031	0.024	0.038	0.204
Province FE	NO	NO	NO	NO	YES

Source: Census of Agriculture and Fisheries 2002 and 2012
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix E Spatial distribution of terrorist activity

Figure E.1: Spatial distribution of terrorist activity between 1991 and 2018